

An Empirical Study on the Business Intelligence (BI) Data Collection Strategy in the ICT-Based Startups in Bangladesh

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Abstract: Business intelligence (BI) has now become a buzz-word in this era of information and communication technology. Data is treated as the fuel for business intelligence. The motive of this paper is to examine the influence of the external antecedents on the selection of BI data collection strategies of the ICT-based startups in Bangladesh. This study developed and analyzed a theoretical model grounded on different external factors that influences the decision to implement two BI data collection strategies (comprehensive and issue-driven) along with one mediator that mediates the relationship of two external antecedents and issue-driven BI data collection. The snowball sampling was used to collect the survey data from experienced BI professionals working in different startups in Bangladesh. The results of the study showed that stakeholders' satisfaction and system quality affect the choice of data collection strategy whereas competitive pressure and institutional isomorphism have no effect on the choice of BI data collection strategy.

Key Words: Business Intelligence; Strategic Decision Making; Startups; ICT, BI Data collection,

JEL Code: M15

1. Introduction

Business intelligence is the systematic way to collect and transform the data into compelling information for improving the decision-making process (Kraemer & Kevin, 2005). BI collects data from several sources for sorting and designing these data in a meaningful and actionable way. BI is being used to measure organizational performance, critically analyze data, predict the perfect modeling for employee management or scaling customer loyalty, data mining, etc. BI keeps all the data in a single central house and decorates it in the simplest way, which helps to surf and navigate the statistics about production, sales, frequency of buying, and so on (Chi, Holsapple, & Srinivasan, 2007). It takes messy information and converts them into tidy and accessible information without relying on others. Now-a-days the use of artificial intelligence (AI) for the analysis of big data has changed the view of BI into a multidimensional phenomenon. Multiple AI systems are being used for the generation of customer data and help to predict as well as influence the purchasing behavior of them (Bhattacharya, 2018). Startups can be defined as starting a new business with new ideas and innovation. As a developing country, several entrepreneurs adapted this unique magic of information management. Pathao, Evaly.com.bd, Shopfront Limited, Othoba.com, Bikroy.com, Truck Lagbe, Hungry Naki,

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Shohoz.com, ShareTrip, and so many ICT-based startups are using business intelligence to process a vast amount of data into simplified a simplified format for the interpretation and complex decision making (Mourshed, Huda, & Haque, 2020). Using BI, employees and the customer can both access data in an organized manner. BI assists strategic decision-making and helps to find out inefficient business processes and hidden patterns. Subsequently, it identifies the rest of the strengths and weaknesses and discovers new opportunities for business which plays a vital role in the improvement of business processes of the startups (Isik, & M, 2010). BI helps those startup organizations to understand the nature of customer and predict future demand, helps to identify customer segments, customer need, decision support, market research, customer collaboration, preferences habit, and anticipate new opportunity to sell that enhance delivering better service (Breslin, 2004; Phan & Vogel, 2010). Some researchers found the effect of BI has a significant positive influence on the organizational performance of the startups (Caseiroa & Coelho, 2017).

2. Theoretical background and hypotheses development

Business intelligence has now become a trendy business management system. Through the recent development of information and communication technology Business Intelligence has gained an extraordinary appeal in the corporate world even though the main concept is not that contemporary (Caseiroa & Coelho, 2017; Tej Adidam, Banerjee, & Shukla, 2012). The origin of the concept came from other fields rather than the business. The basics of business intelligence are being inspired by some intelligence-driven cultures like military intelligence and similar government agencies (Maune, 2014). The term business intelligence is a vast and complex concept to define but most of the scholars of BI concluded it as a mechanism to analyze the data and turn them into valuable managerial knowledge (AL-Shubiri, 2012). It illustrates the process of enhancing the decision-making process through several activities like collection, presenting, analyzing circulating information by the use of advanced ICT (Wanda & Stian, 2015; Lukman, Hackney, Popovič, Jaklič, & Ir, 2011).

ICT-based startups in Bangladesh have shown tremendous growth in recent years. This study has focused on five major external factors that affect two major data collection approaches. Firstly, the comprehensive data collection approach uses massive warehousing of data, collected from several sources and presents them in a general presentable manner. This approach requires massive technical knowledge and infrastructure to process BI data and store them for decision-making purposes (Ariyachandra & Watson, 2010; Watson & Haley, Managerial considerations, 1998; Wang, Li, & Fang, 2018). The second one is the issue-driven data collection approach, which focuses on the collection of data relating to a business problem. Issue-driven BI starts when a business organization searches for the answer to a strategic analytical question and uses the intelligence information system to solve the puzzle (Watson, Wixom, Buonamic, & Revak, 2001; Ram, Zhang, & Koronios, 2016; Mulani, 2013). The BI information management system is a strong problem-solving tool that makes the organization more efficient for exploring new business opportunities. Therefore, issues-driven BI requires an embedded system that is directly linked with business intelligence

with the actual business process of an organization, rather than trying to conduct it separately (Sen & Sinha, 2005).

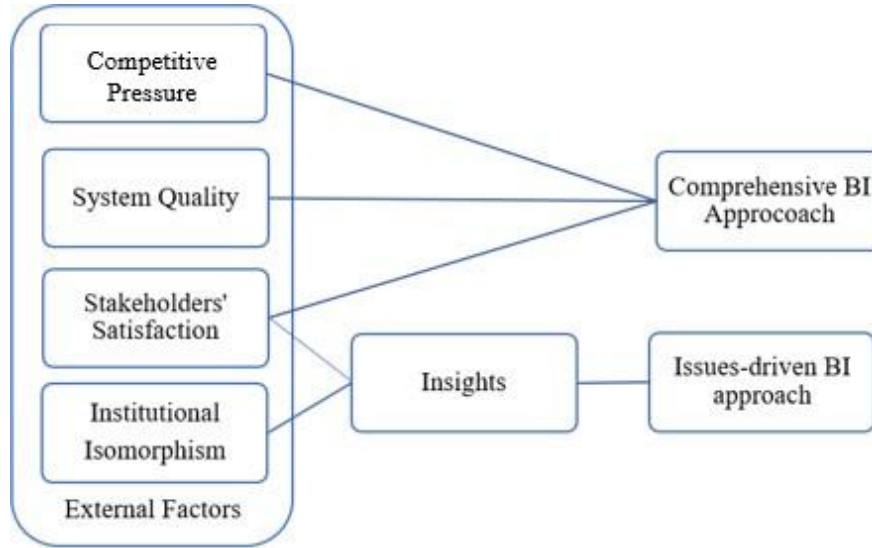


Figure 1 Framework of the study

2.1 Competitive pressure and comprehensive BI approach

Competitive pressure works like a driving tool for an organization to bring innovativeness. It facilitates organizational effort to deal with the business process smartly and efficiently to achieve growth and organizational competitive advantage. Competitive advantage can be defined as the pressure of competitors within the industry (Eidizadeh, Salehzadeh, & Chitsaz, 2017). Competitive pressure drives the organization for giving priority to those attributes which gives much more advantage over a competitor (M. Bradford, 2003).

Business Intelligence identifies the external and internal forces of an organization and shows the pathway of removing the uncertainty of the decision-making process (J.E. Ettlie, 2016). In addition, some shreds of evidence showed that an organization can go for computer-aided technology management for reducing competitive pressure as manually sorting data and managing data are fairly tough for all (C.W. Holsapple, 2005). Several studies show that accepting and implementing the BI system, competitive pressure is one of the influential factors and it helps to improve the prospects of an organization (H. Hwang, 2005; Eidizadeh, Salehzadeh, & Chitsaz, 2017). Based on these discussions we can draw our first hypotheses below:

H₁: Competitive pressure affirmatively influences the selection of comprehensive approach for business intelligence data collection of the ICT startups in Bangladesh.

2.2 System Quality and comprehensive BI approach

The efficiency of a business intelligence system relies much on the quality of the total system. Here, system quality refers to the advanced hardware used in a computer system using which BI data are being collected, stored, and analyzed. BI system delivers an extensive array of functionalities through its integrative package of hardware. A high-quality BI system facilitates data mining hence improve the management of the whole process (Chan & Lau, 2018). Many scholars studied the impact of the quality of the BI system on the collection and analysis of business data. Prior studies found that system quality can be measured through flexibility, reliability, user-friendliness, and response time (McLean, Petter, & Delone, 2014). An improved system quality can increase the security of the data as well as lesser response time which can lead the greater efficiency of the decision-making process (Soilen, Solberg, Anders, & Hasslinger, 2009). To maintain a system that supports a comprehensive BI approach, the system quality should be secured and advanced enough to preserve accuracy and sustainability. Furthermore, system quality also assists to increase the business process productivity (Ales, Hackney, Coelho, & Jaklic, 2012). Hence, the study drawn the second hypothesis based on the literature.

H₂: The system quality of the ICT startups has a positive effect on the decision to select the comprehensive approach for BI data collection.

2.3 Stakeholders' Satisfaction and comprehensive BI approach

Stakeholders are the vital part of the organization who directly or indirectly influences the decision-making process of the organization. Stakeholders kick into the action at every sphere of the organizational business processes. Henceforward, the organization has to consider the satisfaction of the stakeholders for the development of the business intelligence system as well as the collection of the business intelligence data (Gupta, Chen, & Hazen, 2019).

Stakeholders can be delineated by the persons and institutions who have claim over the organization and directly or indirectly affects or affected by the decisions of the organization (McKnight, K, & Linnenluecke, 2016). A number of studies being conducted on the influence of stakeholders on the business intelligence system. Information on primary and secondary stakeholders can be so useful for the current decision-making. It can also add value and precision to future decision-making through in-depth analysis of past data on several issues that are associated with the internal and external stakeholders of a firm (Gupta, Chen, & Hazen, 2019). At present, the use of AI with the BI data is helping the organization to predict not only the future demand but also the features that the customers are looking for. Moreover, it increases organizational sustainability which in return enhances the satisfaction of the stakeholders (Bhattacharya, 2018). A comprehensive approach to data collection provides enough data to AI for decision making which in return enhances the accuracy of business decision making and increases Stakeholders' satisfaction (Bhattacharya, 2018; Ptaschunder, 2020). In the data warehouse, all financial data, sales information, organization's number of people everything can be seen and examine in a single click so the stakeholder might know the

situation about the performance and productivity of the firms at a glance (Simmers, 2004). So here from the above discussion we can hypothetically believe the following:

H3. Stakeholders' satisfaction positively influences the selection of comprehensive BI data collection strategy in the ICT startups in Bangladesh.

2.4 Stakeholders' Satisfaction, insights, and Issues-driven BI approach

At any given moment, a single BI dashboard can have anywhere from 25 to thousands of people viewing it-all with different roles, responsibilities, and various levels of expertise. Stakeholders can access, use, and analyze all these data when they need it. BI and analytic tools are easier-to-use, and necessarily mean that insight is easier-to-understand as well (Mainardes, Alves, & Raposo, 2009). Stakeholders having so many demands on every layer of insights needed from a dashboard so they can identify the reason why pre-configured, plug-and-play solutions might fall short. Using a deeper and personalized understanding of insights, they quickly discover that blanket insights from a chart explainer plug-in are useful or not. Sure enough, companies are highly dependent on BI analysts (Skyrius, Kazimianec, & Žilinskas, 2016). So business intelligence provides all driving factors in time to satisfy all. BI developments have materialized in the form of data-driven approaches for stakeholders that highlight the supply of information for solving issue-driven activities. Big Data diverse sets of data in useful and formerly unknown information supporting insight building and decision making (Parmar, Freeman, Harrison, & De Colle, 2010). So here from the above discussion we can hypothetically believe the following:

H4: Stakeholders' satisfaction provides necessary insight that helps ICT startups to use issue-driven BI data collection strategy.

2.5 Institutional Isomorphism, insights, and Issues-driven BI approach

Institutional isomorphism is the homogeneity of work patterns among organizations and industries. It's a work process where the application, method, and analysis outline are quite similar by nature. This similarity arises from the thirst for achieving the same goal and the compression of identical external forces that are confronted by all the organization like political, social, and technical environmental behavior (Huigang Liang, 2007; Rahadian & Urumsah , 2017). Isomorphism mainly describes the influence of the pressure from the external institutions in the organizational decision-making process. In many cases, organizations have to follow the authoritative guidelines from the regulators which might lead to institutional isomorphism (Ke, Liu, Wei, Gu, & Chen, 2009). For implementing BI in organizations' information processing, institutional isomorphism stimulates the central data store for distinguishing all data based on the data type. As managers are puzzled with information so much, a particular BI system optimizes the decision-making process, data mining, querying, reporting, etc. which reflect the organizations' insight (Burton Swanson & Ramiller, 2004; Ramakrishnan, Jones, & Sidorova, 2012). Startups tend to follow some traditional corporate standards in order to follow industry guidelines. In some cases, not only the startups but also the established businesses tend to follow the best practices of their competitors that they believe to be effective for them as well. (Lai, Cheng, & Wong, 2006). As the insight information is

presenting in a prearranged way, managers come up with issue-driven trends and solutions. In one-way institutional isomorphism revealing the data similarities among competitors and presenting the next best opportunity whereas issue-driven BI approaches get the best possible solution using analytical processing (Olszak & Ziemba, 2006). Hence, institutional isomorphism found to have a positive significant relationship with business intelligence to achieve insightfulness (Rahadian & Urumsah, 2017). Based on the discussions the following hypothesis can be developed.

H₅: Institutional isomorphism helps to achieve insight that facilitates the selection of issue-driven data BI collection strategy.

3. Methodology

To test the hypotheses, the study used a survey method and different statistical analytical software. The survey questionnaire was distributed using both online and offline methods. A paper survey questionnaire was distributed offline and the online survey system 'Typeform' was used for online data collection due to its user-friendly graphical interface. Google Sheet was used to input the data for its cloud storage facility and data security. The demographic analysis and graphical figures were created using MS Excel and IBM SPSS Statistics version 23. Exploratory factor analysis, KMO, and Bartlett's Test were analyzed using SPSS. Path analysis, reliability, validity, and hypotheses were tested using Smart PLS version 3.0

3.1 Design of the research instrument

The survey items were determined through an in-depth analysis of the literature. Items on Stakeholders' satisfaction and system quality were modified from several studies in the context of the BI setting (Petter, DeLone, & McLean, 2015; Adamala & Cidrin, 2011; Rahadian & Urumsah, 2017). Questions regarding competitive pressure were adapted and developed from the widely accepted model of Porter and Millar which was then modified in the context of Business Intelligence by Thong in 1999 (Porter & Millar, 1985; Thong, 1999; Rahadian & Urumsah, 2017). Items related to insights, comprehensive and issues-driven BI approach were settled based on findings and interpretations of prior literature (Mulani, 2013; C., S., & Navathe, 1992; Yi, 2020; Rahadian & Urumsah, 2017) as well as using thorough discussions with BI experts from several ICT based firms in Bangladesh due to the lack of prior validated scales on these variables.

3.2 Population, sampling, and data collection

As of February 2020, more than a thousand startups are now conducting business in Bangladesh having a number of more than 1.5 million employees (Mourshed, Huda, & Haque, 2020). But the number of employees involved with business intelligence is unknown. The study focused on several criteria to select the respondents of the study. First of all, the study focused on selecting participants who have adequate knowledge and experience in this field to comment on the items of the questionnaire (at least two years of experience). Second, the study collected data from the BI developers, analysts, and managers who are direct stakeholders of BI information in the different ICT Startups in

Bangladesh. Total 150 questionnaires were issued and finally, 137 questionnaires were selected with an effect size of 0.27 with a 95% confidence interval which is sufficient enough as the literature suggested to have responses at least four to five times of the items to perform a structural equation modeling (Hair, Risher, Sarstedt, & Ringle, 2018). Seventeen questionnaires were rejected due to inconsistent responses and missing data. The study used a mixed sampling technique to collect the data. Most of the data were collected using a snowball sampling method where respondents referred the questionnaire to other managers and BI professionals using their professional channels. The study also used convenience sampling due to limited mobility as a consequence of the COVID-19 pandemic.

4. Analysis of data

The study used responses from 137 respondents for the final analysis with no missing values. As shown in table 1b, 72 respondents had 2 to 4 years of working experience, among them 57 were male and 15 were female. 54 respondents had experience of 5 to 8 years and 11 respondents had more than 8 years of experience. 76.64% of respondents were male among them 40 respondents had 5-8 years of experience and 8 of them had more than 8 years of working experience.

Table 1a

Case Processing Summary

	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Gender * Years of Experience	137	100.0%	0	0.0%	137	100.0%
Gender * BI Experience	137	100.0%	0	0.0%	137	100.0%

Table 1b

Gender and Years of Experience Crosstabulation

		Years of Experience			Total
		2-4 years	5-8 years	More than 8 years	
Gender	Female	15	14	3	32
	Male	57	40	8	105
Total		72	54	11	137

Many of the respondents were not involved with business intelligence in the first place. Table 1c illustrates the years of job experience and years of BI experience of the respondents. The survey data shows that all respondents having 2 to 4 years of experience BI-related experience from the beginning of their career, which represents the concentration and the vast exposure of the use of business intelligence. 15 respondents having 5 to 8 years of job experience have 2 to 4 years of BI experience. 4 of the respondents having more than 8 years of job experience have 5-8 years of BI experience. About 52.55% of respondents had 2 to 5 years of experience indicating rapid growth of jobs in business intelligence in Bangladesh.

Table 1c

Years of Experience and BI Experience Crosstabulation

		BI Experience			Total
		2-4 years	5-8 years	More than 8 years	
Year of Experience	2-4 years	72	0	0	72
	5-8 years	15	39	0	54
	More than 8 years	0	4	7	11
Total		87	43	7	137

Table 1d

Area of Expertise

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	BI Supportive Activities	6	4.4	4.4	4.4
	Business Analyst	44	32.1	32.1	36.5
	Developer of BI	35	25.5	25.5	62.0
	Evaluating and Purchasing of Relevant technologies for BI	4	2.9	2.9	65.0
	Others	20	14.6	14.6	79.6
	System Maintenance	28	20.4	20.4	100.0
	Total	137	100.0	100.0	

The study used both Exploratory Factor Analysis (EFA) as well as Confirmatory Factor Analysis (CFA) because some constructs used in this study were not validated from previous studies. The study conducted an exploratory factor analysis to identify the number of identical factors in the study whereas, confirmatory factor analysis was conducted to assess the relationship among items of a structural equation. EFA is considered one of the most suited methods to assess the construct validity of items in an empirical study (Bagozzi, 1983; Hair, Anderson, Tatham, & Black, 1998). So, the study used EFA as the first step to examine the validity of the measurement scale. The factor analysis was executed with varimax rotation to examine the construct validity and discriminant validity. Factor analysis examines the items whether they converge together under the suitable factor or not. It also examines whether the items discriminate with several factors or not with minimum cross-loadings (Premkumar, Ramamurthy, & Crum, 1997). The factor analysis was conducted separately for independent variables and dependents variables with mediating variables. The study avoided single factor analysis on all 31 items simultaneously cause, it might not provide a reliable result (Jones & Beatty, 2001; Ramakrishnan, Jones, & Sidorova, 2012).

After running EFA in the dependent, moderating and independent variable separately, KMO and Bartlett's Test suggested that all the three EFA has substantial correlation among them (Appendices Table 1). One item in the independent variable showed high cross-loading which was then removed. After the removal of the item, all the variables in the dependent, moderating, and independent variable showed a factor loading score of

more than 0.5 in the relevant desired factor and less than 0.40 on the other factors. Loading score more than 0.50 on the hypothesized factor and less than 0.40 exhibits enough score for an item to have construct validity (Hair, Anderson, Tatham, & Black, 1998). Eigenvalue and the percentage of variance extracted from independent variables showed that items in the competitive profile have an eigenvalue of 4.33 where institutional isomorphism showed an eigenvalue of 1.443. The percentage of total variance showed that 64.281% of the variance of the independent variable can be explained by these four variables. Conversely, 55.159% of the total variance of the dependent variable can be explained by these two variables of the study (see appendix table 3).

4.1 Measurement Model

After EFA, the study conducted a confirmatory factor analysis (CFA). Although some researchers recommended factor loadings of 0.708 (Hair, Risher, Sarstedt, & Ringle, 2018). But, in some cases in empirical research, loadings above 0.60 are acceptable (Chin, 2010; Hair, Ringle, & Sarstedt, 2011). In the CFA, all the factor loadings of the items had a score of more than 0.60 except for one item in the competitive profile construct. After the removal of the item, the measurement model was run again and all the items had a factor loading score of more than 0.60 which is acceptable for further proceedings (Chin, 2010). To test the reliability of a construct, Cronbach's alpha score of more than 0.70 nevertheless 0.60 is acceptable for exploratory research (Hair, Risher, Sarstedt, & Ringle, 2018). The Cronbach's alpha of the institutional isomorphism is 0.591 where other constructs have more than 0.60 which is sufficient enough to be reliable. Based on the rounding principle of math all the constructs were considered to pass the reliability test including institutional isomorphism. All the constructs have Cronbach alpha less than 0.95 which explains that the constructs didn't compromise content validity (Hair, Risher, Sarstedt, & Ringle, 2018). Composite reliability (CR) also shows that the variables met the composite reliability as all the factors have a CR score of more than 0.70 (Fornell & Larcker, 1981; Chin, 2010). The average variance extracted (AVE) explains the construct validity of a variable. A score of more than 0.50 is recommended for a variable to qualify for the construct validity (Hair, Risher, Sarstedt, & Ringle, 2018). Stakeholders' satisfaction has the highest AVE of 0.709 and other variables have more than 0.50 which represents that all the constructs met the minimum recommended score of AVE.

Table 2

Confirmatory Factor Analysis (CFA) results: Measurement Model

Constructs	Items	Factor Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Competition Pressure	CP1	0.802	0.683	0.824	0.610
	CP2	0.709			
	CP3	0.828			
System Quality	SQ1	0.871	0.818	0.879	0.647
	SQ2	0.679			
	SQ3	0.854			
	SQ4	0.800			
Stakeholders' Satisfaction	SS1	0.840	0.897	0.924	0.709
	SS2	0.843			
	SS3	0.842			
	SS4	0.851			
	SS5	0.833			
Institutional Isomorphism	II1	0.723	0.591	0.785	0.549
	II2	0.760			
	II3	0.740			
Insights	INS1	0.788	0.775	0.855	0.596
	INS2	0.808			
	INS3	0.762			
	INS4	0.728			
Comprehensive BI Approach	CBA1	0.716	0.757	0.837	0.507
	CBA2	0.739			
	CBA3	0.707			
	CBA4	0.764			
	CBA5	0.628			
Issues-driven BI approach	IBA1	0.731	0.821	0.874	0.582
	IBA2	0.752			
	IBA3	0.839			
	IBA4	0.714			
	IBA5	0.773			

Fornell-Larcker criterion was calculated to test the discriminant validity in this study. In the Fornell-Larcker criterion, the squared root of the AVEs should be higher than the correlation value among the latent constructs in order to have discriminant validity (Hair, Risher, Sarstedt, & Ringle, 2018; Fornell & Larcker, 1981). As shown in table 3a, all the AVEs (diagonal values) of the constructs are higher than the non-diagonal values

representing the correlations among the latent variables. Hence, the constructs achieved discriminant validity and the constructs can be moved for further analysis.

Table 3a

Discriminant Validity (Fornell–Larcker Criterion)

	CBA	CP	IBA	II	INS	SQ	SS
CBA	0.712						
CP	0.033	0.781					
IBA	0.146	0.269	0.763				
II	0.025	0.034	0.172	0.741			
INS	-0.048	0.039	0.362	0.129	0.772		
SQ	0.482	-0.161	-0.446	-0.243	-0.315	0.804	
SS	0.509	0.13	0.655	0.243	0.269	-0.232	0.842

The study the heterotrait-monotrait ratio of correlations (HTMT) to test the discriminant validity, as HTMT proved to be more efficient than the Fornell-Larcker criterion or the assessment of the cross-loadings through Monte Carlo simulation (Henseler, Ringle, & Sarste, 2015). Based on the HTMT ratio of the study, all the constructs have HTMT ratio less than 0.85 as recommended in several studies for theoretically different constructs (Hair, Risher, Sarstedt, & Ringle, 2018; Henseler, Ringle, & Sarste, 2015).

Table 4b

Discriminant Validity (HTMT Criterion)

	CBA	CP	IBA	II	INS	SQ	SS
CBA							
CP	0.135						
IBA	0.227	0.354					
II	0.187	0.164	0.256				
INS	0.205	0.091	0.441	0.191			
SQ	0.574	0.211	0.551	0.341	0.400		
SS	0.621	0.176	0.772	0.340	0.314	0.298	

4.2 Structural model (hypotheses testing)

The study used Smart PLS version 3.3.2 to draw and analyze the structural equation modeling (SEM) due to its capability to evaluate series of interconnected dependent relationships simultaneously (SmartPLS Version 3.3.2, Ringle, Wende, & Becker, 2015). The graphical depiction of the SEM is given in *Figure 2*.

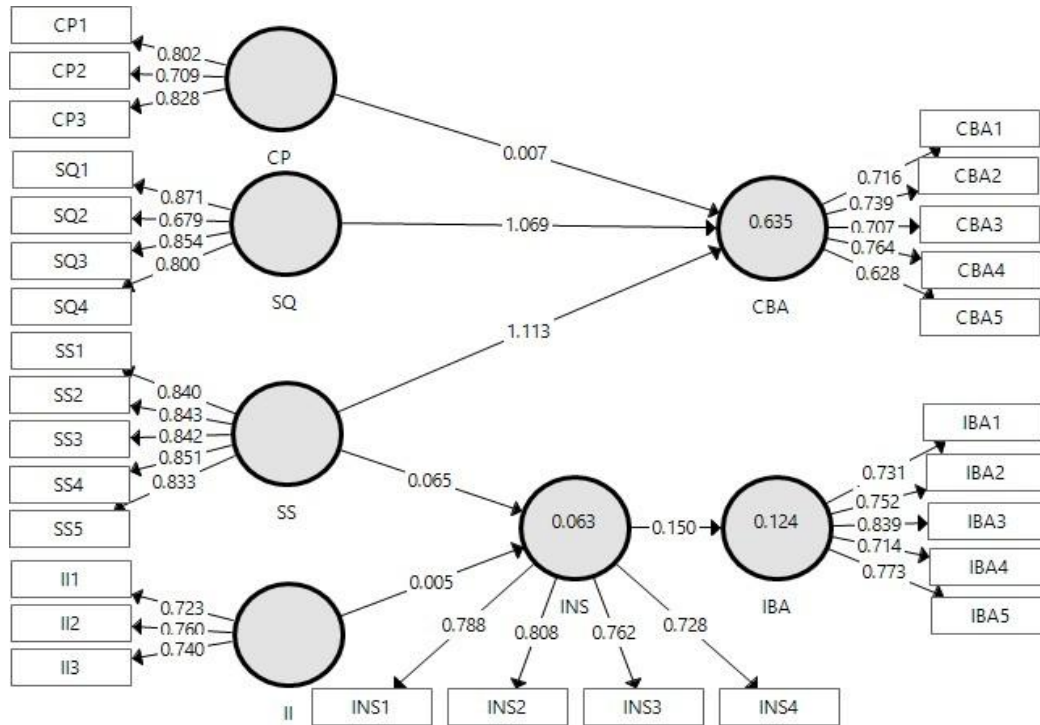


Figure 2 PLS results for hypotheses tests

In the illustration, the inner model shows the value of f-square, the outer model shows the value of outer weights or loadings, and the inner constructs show the adjusted R squared.

The study used recommended bootstrapping for the sample size of 5000 samples (Hair, Risher, Sarstedt, & Ringle, 2018). As the hypotheses are unidirectional in nature, the calculation was conducted using a one-tailed t-test. Table 5 shows the path coefficient, Standard error, t statistics, p-value, and bias-corrected confidence interval to provide a proper reaction to the hypotheses.

Based on the framework of the study, there were four independent variables, two dependent variables, and one mediator for one dependent variable. Five hypotheses were developed based on the literature. To declare a relationship statistically significant, t value should be higher than 1.96, the p-value should be less than 0.05 and there shouldn't be any zero between the bias-corrected confidence interval (Benitez, Henseler, Castillo, & Schuberth, 2020; Hair, Risher, Sarstedt, & Ringle, 2018). As shown in the path coefficient analysis, stakeholders' satisfaction (SS) and comprehensive BI approach (CBA) have a statistically significant positive relationship ($H_3: \beta = 0.651, t = 16.752, P < 0.000^{***}$). Similarly, the relationship between system quality (SS) and comprehensive BI approach (CBA) was found to be positive ($H_2: \beta = 0.642, t = 9.01, P < 0.000^{***}$). Therefore, these two hypotheses are accepted based on their significance. Conversely, the relationship between competitive profile (CP) and comprehensive BI approach (CBA) is not statistically significant based on the p-value as well as bias-corrected confidence

interval (H_2 : $\beta = 0.052$, $t = 0.659$, $P < 0.255$). Thus, the second hypothesis of the study can be rejected. The relationship between stakeholders' satisfaction (SS) and insight (INS) was also found to be statistically significant ($\beta = 0.253$, $t = 2.236$, $P < 0.013$) where the relationship between institutional isomorphism (II) and insight (INS) was found to be insignificant based on the value of t statistics, p -value and bias-corrected confidence interval ($\beta = 0.067$, $t = 0.705$, $P < 0.240$). In addition, the relationship between insight and issue-driven BI approach was found to be highly significant ($\beta = 0.362$, $t = 3.585$, $P < 0.000^{***}$). The specific indirect effect shows, that the effect of mediating variable between the relationship of institutional isomorphism and issue-driven BI approach is statistically insignificant with a p -value of 0.251 ($\beta = 0.024$, $t = 0.672$). Moreover, the mediating effect of insight between stakeholders' satisfaction and the issue-driven BI approach was also found to be insignificant ($\beta = 0.091$, $t = 1.374$, $P < 0.085$).

Table 5a

Path coefficient

Paths	Beta	Standard Error	t statistics	p values	Bias Corrected Confidence Interval	Results
CP → CBA	0.052	0.079	0.659	0.255	[-0.102, 0.161]	Not supported
II → INS	0.067	0.096	0.705	0.240	[-0.247, 0.147]	Not supported
INS → IBA	0.362	0.101	3.585	0.000 ^{***}	[0.194, 0.502]	Supported
SQ → CBA	0.642	0.071	9.01	0.000 ^{***}	[0.515, 0.748]	Supported
SS → CBA	0.651	0.039	16.752	0.000 ^{***}	[0.582, 0.711]	Supported
SS → INS	0.253	0.113	2.236	0.013 ^{**}	[0.058, 0.431]	Supported

Table 6b

Specific indirect effect

	Beta	Standard Error	t statistics	p values	Bias Corrected Confidence Interval	Results
II → INS → IBA	0.024	0.036	0.672	0.251	[-0.091, 0.055]	Not supported
SS → INS → IBA	0.091	0.066	1.374	0.085 [*]	[0.009, 0.214]	Not supported

Legend: CP→competitive pressure; II→institutional isomorphism; INS→insight;

SQ→system quality; SS→stakeholders' satisfaction; CBA→comprehensive BI approach; IBA→Issue-driven BI approach.

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$

5. Discussions

As per the results, the hypotheses in the framework of this study were partially supported. System quality and the stakeholders' satisfaction confidently affect the decision to adopt a comprehensive data collection strategy for business intelligence. Moreover, institutional isomorphism and stakeholders' satisfaction do not have any influence to adopt an issue-driven BI data collection strategy to achieve insightfulness. These results have given an interesting understanding of the influence of industry standards and authoritative guidelines on the reasons to adopt the issue-driven approach for data collection by the ICT-based startups in Bangladesh. Most of the startups decide to adopt this approach not to achieve insightfulness. Rather, they might have using this approach as a preliminary goal (Ramakrishnan, Jones, & Sidorova, 2012). Another possible explanation could be, the startups are now adopting comprehensive data collection strategy due to the massive use and capacity of modern technology to deal with big data to find the answer to the business problem why did it happen or predict the problem before it occurs rather look for what happened after any external or internal event. Thus, the link between institutional isomorphism on issue-driven data collection does not comply with the operational standard of the startups in Bangladesh.

In addition, the achievement of insightfulness tends to have no mediating effect on the relationship between stakeholders' satisfaction and issue-driven data collection in the ICT-based startups in Bangladesh. The possible explanation behind this could be, the most of the people in a third-world nation like Bangladesh are tech-savvy. Furthermore, the lack of a simplified communication channel provided by the ICT Startups hinders the willingness of stakeholders to provide insight to choose issue-driven business intelligence data collection.

More and more startups are now using a comprehensive BI data collection strategy to forecast the future trends of their business. The enormous use of artificial intelligence (AI), the internet of things (IoT), big data for data mining are now trending especially in ICT-based businesses. This drift has shifted the selection of the data collection strategy of the business. Better system quality allows the IT experts to use a comprehensive model of data collection as an effective medium. Additionally, stakeholders are also playing a vital role to choose comprehensive data collection as time demands to be a proactive business process to survive in this competitive business environment. Competitive pressure does not have any significant effect on choosing a comprehensive data collection strategy based on the research data. Most of the ICT-based startups are innovative and unique in nature. This might have caused a major reason behind this result.

6. Research gap and limitations

As given in the framework there were three levels of the study. The first level describes the external factors that influence the selection of BI data collection. The second level has one mediator that facilitates the selection of the issue-driven BI data collection approach. The last third level consists of BI data collection strategies. The wave of the information and communication revolution in Bangladesh is pretty new. Therefore, few professionals have experience of more than 5 years as discussed earlier. The first challenge of this

study to find proper respondents who have enough knowledge about all three levels. Therefore, the study was able to manage 137 responses although this kind of study requires a vast number of samples to draw a more accurate comprehensive analysis. On other hand, the study required more responses from business professionals although very few business professionals know all three levels in the study. As discussed before, stakeholders' satisfaction and institutional isomorphism doesn't provide enough insight for the selection of issue-driven BI data collection strategy. Therefore, further studies need to be conducted to find the factor that influences the issue-driven data collection strategy.

7. Conclusion

As per the demand of the modern era of information technology, a number of Bangladeshi organizations are shifting from traditional business models to IT-enabled business models. It has also paved the way to grow more and more ICT-based startups in Bangladesh. Therefore, these startups highly rely on business intelligence data rather than the traditional data collection approach. For that purpose, startups have to decide strategic choices like data collection strategies considering the diversified external factors. Through analysis of the previous studies, this study developed and examined a theoretical model to discover the influence of the antecedents influencing the choice of BI data collection strategy. The results suggested that system quality and stakeholders' satisfaction influence the strategic decision to choose a comprehensive BI data collection strategy. Alternatively, competitive pressure doesn't have any influence to choose a comprehensive data collection strategy for the startups in Bangladesh. As per the prior literature, the study drew hypotheses that stakeholders' satisfaction and institutional isomorphism influences the achievement of insightfulness which in turn positively affects issue-driven BI data collection strategy. Surprisingly, both the cases do not have any influence over the selection of issue-driven data collection strategies for the ICT-based startups in Bangladesh. The study believes to have high implications for both researchers and practitioners. The study can be a helpful base for researchers to conduct a more comprehensive analysis using more external factors, mediators, and moderators. Moreover, as the ICT-based business industry in Bangladesh is still in its teenage, this research can be a guidebook for industry experts to choose appropriate BI data collection strategy for their business. Apart from this, organizations involved in banking, finance, FMCG, manufacturing, retailing can get benefits from this study for the strategic decision to implement business intelligence in their organization. This study may be used as an initial tool for businesses willing to implement business intelligence in their business processes.

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Appendices:

Appendix Table 1 KMO and Bartlett's Test of Independent, Mediating and Dependent Variables

KMO and Bartlett's Test			
	Independent Variable	Mediating Variable	Dependent Variable
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.817	.782	.820
Bartlett's Test of Sphericity Approx. Chi-Square	807.575	135.130	373.071
df	120	6	45
Sig.	.000	.000	.000

Appendix Table 2 Communalities of Independent, Mediating and Dependent Variables

Communalities								
Independent Variable			Mediating Variable			Dependent Variable		
Items	Initial	Extraction	Items	Initial	Extraction	Items	Initial	Extraction
CP1	1.000	.527	INS1	1.000	.586	CBA1	1.000	.545
CP2	1.000	.601	INS2	1.000	.651	CBA2	1.000	.525
CP3	1.000	.624	INS3	1.000	.567	CBA3	1.000	.484
CP4	1.000	.635	INS4	1.000	.586	CBA4	1.000	.577
SQ1	1.000	.756				CBA5	1.000	.428
SQ2	1.000	.592				IBA1	1.000	.575
SQ3	1.000	.696				IBA2	1.000	.570
SQ4	1.000	.648				IBA3	1.000	.678
SS1	1.000	.709				IBA4	1.000	.545
SS2	1.000	.699				IBA5	1.000	.589
SS3	1.000	.741						
SS4	1.000	.719						
SS5	1.000	.683						
II1	1.000	.536						
II2	1.000	.545						
II3	1.000	.575						

Extraction Method: Principal Component Analysis.

Appendix Table 3 Total Variance Explained (Independent variables)

Component (Independent Variables)			Component (Mediating Variables)			Component (Dependent Variables)									
Items	Loadings	Eigenvale (% of Variance)	Items	Loadings	Eigenvale (% of Variance)	Items	Loadings	Eigenvale (% of Variance)							
CP1	0.699	4.333 (27.084)	INS1	0.766	2.390 (59.76)	CBA1	0.737	3.224							
CP2	0.772		INS2	0.807		CBA2	0.723	(32.243)							
CP3	0.76		INS3	0.753		CBA3	0.696								
CP4	0.791		INS4	0.766		CBA4	0.759								
SQ1	0.844	2.450 (15.316)				CBA5	0.624								
SQ2	0.721					IBA1	0.727	2.292							
SQ3	0.825					IBA2	0.754	(22.916)							
SQ4	0.767					IBA3	0.82								
SS1	0.836	2.058 (12.862)				IBA4	0.73								
SS2	0.831					IBA5	0.766								
SS3	0.834														
SS4	0.835														
SS5	0.81														
II1	0.705	1.443 (9.021)													
II2	0.711														
II3	0.752														

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.